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ABSTRACT

Validity data were collected on tests from five aptitude clusters: information-processing (IP) componential skills, IP metacomponential skills, practical intellectual skills, cognitive flexibility, and cognitive speed. In addition, the IP activities underlying learning were elucidated. IP componential data were derived via two approaches. The first approach involved collecting data on subjects' eye movements during solution of reasoning task items, with a corneal reflectance eye tracking system, and using eye movement indices of IP as predictors of Armed Forces Qualifying Test (AFQT) and school performance. The second approach involved presenting isolated IP components on separated computer screens. The computer display was under the experimental subject's control. Comparable IP data were derived from both approaches. In all, 6 studies were conducted with 66, 33, 39, 68, 67, and 41 Navy recruits, respectively. Predictors from these aptitude domains were validated against the AFQT and four measures of performance in Navy basic electricity and electronics school (NBEES): time needed to complete each instructional module; final average; total contact time; and number of remediations of each source module. Data indicate that tasks from all five clusters, as well as IP components of learning, are significant predictors of AFQT and NBEES performance. Nine data tables and a 35-item list of references are included. Appendix A gives data on 11 IP indices derived from eye movement data, and Appendix B gives data on 3 IP indices derived from multiple-screen data. (Author/RLC)

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INFORMATION-PROCESSING INDICES OF INTELLIGENCE AMONG NAVY PERSONNEL

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Abstract

Validity data were collected on tests from five aptitude clusters. These clusters are (a) information-processing componential skills, (b) information-processing metacomponential skills, (c) practical intellectual skills, (d) cognitive flexibility, and (e) cognitive speed. In addition, the information-processing activities underlying learning were elucidated. Information-processing componential data were derived by means of two approaches. The first approach involved collecting eye movements during solution of reasoning task items, with a corneal reflectance eye tracking system, and using eye movement indices of information processing as predictors of AFQT and school performance. The second approach involved presenting isolated information-processing components on separate computer screens. The computer display was under the experimental subject's control. Comparable information-processing data were derived from both approaches. Predictors from these aptitude domains were validated against the Armed Forces Qualifying Test (AFQT) and four measures of performance in Navy Basic Electricity and Electronics school. The four school performance measures were (a) time needed to complete each instructional module, (b) final average, (c) total contact time, and (d) number of remediations of each course module. Data indicate that tasks from all five clusters, as well as information-processing components of learning, are significant predictors of AFQT and Navy basic electricity and electronics school performance.

INTRODUCTION

Problem

The purpose of this effort is to validate a set of experimental aptitude clusters of tests against AFQT and navy Basic Electricity and Electronics school performance. This work is consistent with a broader goal of numerous research psychologists to elucidate the information-processing substrate of intelligence. This goal has theoretical and applied motivations. From the standpoint of advancing theory, a major thrust among intelligence researchers is to strive to understand intelligence in terms of the fundamental information-processing activities that underlie differences in scores on cognitive tasks or tests involving mental operations such as reasoning. With regard to the application of intelligence research to measurement of intellectual operations, this research program offers a set of aptitudes that, by themselves, account for significant amounts of variance in test batteries of Navy aptitude (e.g., AFQT) and in measures of Navy school performance. Moreover, the approaches offer significant incremental validity for predicting school performance when used in

conjunction with the aforementioned Navy test battery. In terms of both theory and application, this effort provides new techniques for deriving information about information-processing componential and metacomponential skills as well as a set of newly studied cognitive dimensions.

Purpose

The general purpose of this effort is to determine if the performance of Navy personnel can be predicted successfully using a five-prong theoretical framework of intelligence. The five aptitude clusters in the framework tap (a) componential abilities, (b) metacomponential abilities, (c) information-processing substrate of flexibility, (d) information-processing substrate of learning, and (e) cognitive speed. The effort has 14 interrelated specific purposes. These specific purposes are enumerated below, followed by discussion of expected hypotheses for each purpose. The manner in which objectives are operationalized and the specific hypotheses guiding the work are discussed in the Method section.

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1. Validate the cluster of information-processing componential abilities, ascertained by recording ongoing eye movement patterns, against both aptitude test performance and school performance.
2. Validate the cluster of information-processing componential abilities, derived from the multiple-screen, computer-based testing method, against AFQT.
3. Compare componential models of AFQT performance derived from both testing paradigms.
4. Assess the incremental validity that results from coupling information-processing componential measures with AFQT to predict school performance.
5. Validate the metacomponential skills of metamemory and practical intelligence against AFQT performance.
6. Validate the metacomponential cluster of aptitudes against school performance, comparing metacomponential models of school performance.
7. Assess the incremental validity that results from coupling metacomponential measures with AFQT in predicting school performance.

8. Validate the flexibility measures against AFQT performance.
9. Validate the flexibility measures against school performance.
10. Assess the incremental validity that results from coupling flexibility measures with AFQT in predicting school performance.
11. Validate measures of cognitive speed against AFQT performance.
12. Validate measures of cognitive speed against school performance.
13. Assess the incremental validity that results from coupling cognitive speed measures with AFQT in predicting school performance.
14. Assess the incremental validity that results from coupling information-processing componential measures with measures of cognitive speed in predicting AFQT and school performance.

The aptitudes under investigation are validated against the Armed Forces Qualifying Test (AFQT) and against school performance. Four measures of school performance are used. These measures are (a) contact time, (b) time devoted to

each subject-matter module, (c) number of remediations, and (d) final average. The aptitude framework taps five clusters of aptitudes. The first cluster includes information-processing componential skills. In this regard, the importance of rule inference, rule application, and confirmation to intelligent performance are ascertained. Strategy components such as the point in processing at which the first attempt at response selection occurs, the number of times ongoing processing is broken to attempt response selection, the amount of information an individual can process at a given time, and the speed with which these operations are executed also are isolated. The second cluster taps metacomponential (i.e., executive processing) activities. Tests in this cluster center on task-prioritization skills and metacognitive activities. The third domain centers on measures of cognitive flexibility. In this regard, interest in this effort is in the ability to maintain processing efficiency when the demands of the experimental test change. The fourth domain taps information-processing indices of learning. Changes in processing efficiency over blocks of trials are isolated. These four clusters derive from work conducted under earlier contracts awarded to Dr. R. Dillon (in press-a, in press-b).

The fifth cluster in this framework taps cognitive speed. The choice reaction-time tasks in this cluster are taken from tests used by Dr. Gerald Larson at NPRDC. The predictive power of componential operations and of cognitive speed measures are tested separately herein, although later interest in cognitive speed is in linking the speed and consistency of speed with which individuals solve simple cognitive tasks (e.g., choice reaction-time measures) to the efficiency with which those individuals process information during solution of complex inductive reasoning problems.

Background

The study of human intelligence has suffered from certain limitations. Most conceptualizations of intelligence have been quite narrow, centering on a small number of domains (i.e., often only one domain), with the domains being formulated narrowly. For example, researchers may devote their attention to one type of ability (e.g., spatial ability) or, more narrowly, to only one aspect of ability, such as dynamic spatial ability or mental rotation. As a consequence, our knowledge regarding the nature of intelligence has not broadened as it might otherwise. Moreover, the importance of new aptitudes research is

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underscored by examination of the less-than-satisfactory estimates of who will succeed in given military, academic, or occupational training programs or in particular professional settings that are derived from typical frameworks for predicting intelligent performance. The relatively narrow focus of most testing programs has played a major role in the inability of existing testing efforts to account satisfactorily for variation in intelligent school or job performance.

The investigation of human intelligence is motivated by two complimentary goals, both necessitating accurate measurement of intellectual processes. The theoretical goal is to advance knowledge regarding the nature of mental representations. The importance of the applied goal of enhancing prediction of training, academic and/or occupational success in military selection and classification cannot be overstated. Scientists are not able to advance knowledge regarding the nature of intelligence or improve prediction of success in military enlisted or officer training programs in the absence of sensitive measurement of information-processing and learning abilities. The need for improved prediction of who will succeed in military careers, and for possession of

mechanisms for distinguishing average potential from the potential for excellence is clear. Resources are saved on the part of students or enlisted personnel to the extent that diagnosticians can avoid selecting learners for programs in which they are not likely to succeed or selecting individuals for jobs in which they are not likely to perform well. Resources also are saved on the part of the military organization if attrition and the associated personnel and other costs therewith can be minimized.

Despite the major importance of accurate selection mechanisms for training and job placement, sizable rates of attrition continue to constitute a major problem in the military sector. An increasing number of psychologists are displaying an interest in developing improved testing procedures (cf. Dillon, 1986, in press-a, in press-b; Sternberg, 1984). These and other investigators contend that typical psychometric assessments rarely account for satisfactory amounts of variance in measures of academic success or other criterion measures of interest (e.g., Dillon, 1985, 1986; Jencks, 1977; Matarazzo, 1972; McCall, 1977; Wechsler, 1975). Moreover, diagnostic and prescriptive information available from traditional assessments is imprecise because models used for prediction

are comprised of predictors taken from one or more test scores which measure only the products of performance. Thus, no information is available with respect to strengths and limitations in the processes underlying performance. The importance of such information is clear. Very different patterns of information-processing strengths and limitations underlie the same test score.

A robust conceptual framework for measuring and understanding intelligence, and for predicting intelligent performance is needed. Clearly, a crucial need exists for enhanced prediction of success of training among Navy personnel, and a theoretical model will provide the framework necessary for implementation of the needed testing program. The work completed under this ongoing effort is designed to address this need. Previous research activities, conducted by Dr. R. Dillon and centering on the aptitude dimensions studied in the present effort, are summarized below.

Componential Operations: Eye Movement Technique

The eye movement work involves recording eye scan patterns during solution of intact, complex reasoning items. In initial validation efforts, Dillon (see 1982) established

the usefulness of recording eye movement patterns during solution of reasoning items for which difficulties and other characteristics of distinct information-processing stages were manipulated. Interpretable differences in the sequence of eye movements during solution of stages having particular characteristics provided a means of important validation for the eye movement information-processing technique. This approach has yielded a substantial amount of information regarding the nature of intellectual processes (see also Dillon, 1987-a, 1987-b, 1987-c, 1987-d, in press-a, in press-b).

Four levels of individual differences in information-processing components were isolated in the earlier work mentioned above that underlie, and thus significantly predict, intelligent performance. These levels tap individual differences in (a) execution of distinct information-processing stages, (b) the order in which processing steps are executed, (c) execution of optional strategy elements, and (d) changes in processing over time. In addition, the contribution of relevant declarative knowledge, abilities to induce or deduce the transformational rules governing relations among stimulus elements, and abilities to manipulate stored verbal,

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visuospatial and, as relevant, quantitative stored knowledge were isolated in this work. Information-processing indices, derived from earlier eye movement studies and used in this work, are described in Appendix A.

Through research conducted in Dillon's laboratory (e.g., Dillon, 1982, 1985, 1986, 1987-a, 1987-b; Dillon & Reznick; Dillon & Stevenson-Hicks, 1981; Dillon & Wisher, 1981) she has demonstrated that eye movement measures of information processing, recorded during solution of intact inductive reasoning items, account for markedly greater amounts of variation in measures of academic achievement or training success than do scores taken from the same items, with R^2s in the 20s for test scores and in the mid-40s to high-70s for information-processing measures.

Componential Operations: Multiple- Screen Technique

A multiple-screen, computerized testing procedure was used in this effort. The procedure is designed to provide data on information-processing operations to corroborate information available through the eye movement recording technique. Information-processing data, derived from this approach and used in this effort, are described in Appendix B.

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Metacomponential Operations

With regard to metamemory processes and practical problem-solving abilities, Dillon and a colleague reported data from studies completed recently that indicate that subjects differ in their tacit acquisition of task prioritization skills as a function of area of training, with subjects from highly structured disciplines exhibiting less task prioritization skill compared to individuals from less structured domains (Dillon & Lyerla, 1986). Moreover, Dillon reported that metamemory and practical problem-solving abilities contribute significantly to academic success (Dillon, Lyerla, & Aubertin, 1987).

Flexibility

The third domain of cognitive aptitudes investigated in this collaborative program of research centers on the multidimensional construct of cognitive flexibility. Academic and professional success necessitate possession of many and varied abilities and skills. Beyond possession of specific skills, an important set of competencies underlying intelligent (i.e., successful) performance is believed to involve the cognitive flexibility with which processes are

executed. Dillon (in press-a, in press-b) describes the abilities to (a) utilize an approach requested by the experimenter when more than one approach is potentially appropriate, (b) generate more than one strategy in solution of test items or problems that have more than one effective strategy, and (c) change approach when the demands of the task change.

Despite the considerable recent interest in cognitive flexibility that has been displayed in the literature (e.g., Cooper, 1980, 1982; Cooper & Mumaw, 1985; Gitomer, 1984; Lesgold, Feltovich, Glaser, & Wang, 1981; Lohman & Kyllonen, 1985; Schneider & Fisk, 1986; Scribner, 1984), no framework exists for studying flexibility. Dillon (1987-d, in press-a) has undertaken a program of research to operationalize a multifaceted theory of flexibility and to determine its relations to success among students and professionals. She believes flexibility involves the abilities to (a) generate multiple strategies for cognitive problems or test items that can be solved in more than one way, (b) analyze and/or synthesize incomplete information to maximize interpretations possible, (c) maintain information-processing efficiency during solution of items that require utilization of different types of

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transformational rules for their solution, and (d) change set in order to generate new and different solutions to problems that follow sets of items that were different than the current item. With respect to this last aspect of cognitive flexibility, the experimenter tells the subject which type of strategy or classificatory scheme to use, whereas in the second type of flexibility, the task demands change across items, with only one type of transformational rule governing a particular item. In previous work, Dillon and her colleagues reported that the ability to generate multiple strategies during solution of complex inductive reasoning tasks that can be solved in more than one way contributes significantly to academic success among college students in professional education (Dillon, Lyerla, & Aubertin, 1987).

Cognitive Speed

Attention, on the part of some scientists, has been devoted to cognitive speed. This attention stems from an interest on the part of a number of experimental psychologists in (a) understanding information-processing speed, (b) elucidating the role of cognitive speed in models of intelligence, and (c) using cognitive speed

indices along with measures of more complex intellectual activities to predict intelligent school or job performance. Recent work is cited in Larson (1985).

Interest in cognitive speed in this effort is two-fold. First, the relationship of cognitive speed to Armed Forces aptitude measures is of interest. A second interest is in the role of cognitive speed to the amount of time required to complete Navy Basic Electricity and Electronics School. Subsequent work is being planned to elucidate the information-processing locus of cognitive speed by relating speed indices to information-processing components of complex inductive reasoning. Moreover, efforts are planned that will enable researchers to assess the incremental validity of models comprised of information-processing components and cognitive speed indices relative to the validity of information-processing measures alone.

METHOD: COMPONENTIAL CLUSTER

Aptitude measures in the componential cluster are selected to permit researchers to ascertain the role of individual differences in information-processing activities to aptitude test and school performance. Two methods are

used to study these activities. The first paradigm involves recording eye movement patterns during task solution. The second approach involves using subject-controlled movement through a series of computer screens, each screen containing information relevant to an individual information-processing stage. These procedures are described below.

Componential Cluster: Eye Movement Recording

Sample

The sample was comprised of 68 Navy recruits. (Final school average and AFQT data together were available for 66 subjects.) All examinees had normal uncorrected or corrected vision.

Instruments

Two instruments were used. The first instrument was comprised of 15 items taken from the Advanced Progressive Matrices (Raven, 1962). Each item was a 3 x 3 figural analogy with a missing portion in the lower right segment of the main stimulus array. An 8-item response set was located

below the main stimulus array in each item. The examinee's task was to select the response option that correctly completed the stimulus array.

The second instrument was part of Form A of the Inductive Reasoning Test (Dillon & Radtke, 1985). Four types of complex verbal items, two sets of complex verbal analogies and two sets of complex verbal classifications, were used. The Inductive Reasoning Test's two sets of figural items were not used. The rules governing the relations among stimulus elements in two of the item sets were semantic, while the relations governing stimulus elements in two of the sets of items were grammatical (e.g., number of letters).

Hypotheses

Intelligent aptitude test performance and successful school performance among Navy personnel are hypothesized to be related to information-processing that is efficient and rule governed. Individual differences at four levels reflect this rule-governed, efficient nature.

First, intelligent test and school performance are functions of the examinee's allocation of processing resources to the different stages of information processing.

In this regard, intelligent performance is expected to be reflected in allocation of a relatively large percentage of resources to encoding/inference activities and a relatively small percentage of resources to confirmatory activities.

Second, intelligent processing is reflected in the order in which information-processing activities are executed. In this regard, the present effort focuses on the point during solution of each test item at which the initial break in ongoing processing occurs, to attempt response selection. The hypothesis, confirmed in earlier work cited previously, is that the later in processing this initial break occurs, the more rule-governed the processing and, thus, the higher the aptitude test and school performance.

Third, intelligence is manifested in the execution of other strategy components. In this effort, the number of breaks in processing across test items, the total number of units of processing, and the size of processing units are hypothesized to relate to intelligent performance, with the first two variables being negatively weighted and the third variable being positively weighted (i.e., larger units are positively related to test and school performance).

Fourth, interest is in gross adaptations over time. The manner in which processing efficiency increases over

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time reflects aptitude. Specifically, significant increases in information-processing efficiency are expected to be positively related to aptitude test and school performance.

Procedure

Items from the APM were ordered randomly for presentation. Items from the Inductive Reasoning Test (Form A) were presented in subtests.

Each item was presented in the form of a 35 mm slide, administered on a rear-screen projector. The Whittaker 1992 was used to track eye fixations. The experimental subject's head was positioned against chin and forehead rests. An eye-level screen was viewed from a distance of 57cm. The pupil-centered, corneal reflectance system computed the subject's point-of-regard from two (i.e., horizontal and vertical) reference points at 60Hz. Subtended visual angle was 12 deg in both vertical and horizontal directions. An eye fixation was defined by the absence of change in eye position exceeding 1 deg for a period of at least 125msec. Calibration of eye tracking was monitored and corrected if necessary following the subject's response to each test item.

Componential Cluster: Multiple-Screen Technique

Sample

The sample was comprised of 33 Navy recruits.

Instrument

The verbal subtests of Inductive Reasoning Test items (Form B) were used herein.

Hypotheses

The hypotheses associated with the multiple-screen componential technique parallel the hypotheses stated above for the eye movement technique. Encoding/rule inference, rule application, and confirmation stages are explained. Information regarding the point in processing at which the initial attempt at response selection is made, and information with respect to the total number of breaks in processing also are available.

Procedure

Isolation of encoding/rule inference, rule application, and confirmation information-processing activities is accomplished by means of a paradigm that involves use of a

partial screen technique, with movement between computer screens being under the experimental subject's control (see Dillon & Wolfe, 1987).

Complex reasoning items are decomposed into distinct information-processing stages for item administration, and each stage is displayed on a separate computer screen. Subjects move forward and backward between stages, processing information about each stage as many times and for as much time as necessary for item solution. The procedure is designed to yield information to corroborate data available through Dillon's eye movement paradigm (see Dillon, 1982, 1986, in press-a, in press-b for reviews of this work).

Metacomponential Cluster

Metacomponential operations concern those mental activities in which subjects engage when they are thinking about their mental processes, planning to engage in problem solving, and/or monitoring solution processes.

Sample

The sample was comprised of 39 Navy recruits.

Instruments

General planning and monitoring activities were examined using two instruments. The first measure required examinees to judge the frequency with which they engaged in various memory-directed tactics for different memory outcomes. The second instrument provided a measure of the examinee's practical problem-solving abilities, social competence, and practical verbal intelligence.

Hypotheses

An impressive literature exists (see Sternberg & Wagner, 1986 for recent work in thinking in applied contexts) that points to the important roles of planning, monitoring, and other metacognitive activities in intelligent performance. Metamemory and practical problem-solving abilities are hypothesized to play positive roles in successful test, school, job, and everyday performance. The two metacognitive measures investigated in this effort are expected to contribute to aptitude-test and school performance.

Procedure

The order of test administration for the two metacognitive tasks was counterbalanced. For the metamemory instrument, examinees were instructed to rate the frequency with which they used memory-directed tactics, for example, sentential elaboration, rehearsal, notetaking, and interactive imagery, when trying to accomplish a variety of learning outcomes. Outcomes included word spellings, word meanings, and the main points of stories. For the practical problem-solving instrument, subjects rated the extent to which their intellectual performance embodied sets of practical skills relating to verbal, social, and practical problem-solving competencies.

Cognitive Flexibility

Cognitive flexibility is defined in this context as the ability to maintain information-processing efficiency when task items are presented that have different demands than blocks of previously presented items. Examinees must flexibly break cognitive sets developed previously and induce new sets of rules.

Sample

The sample was the set of 68 examinees who were tested under the eye scan recording paradigm.

Instrument

Similarities in information-processing efficiency, across sets of different types of items from the Inductive Reasoning test, were used to assess cognitive flexibility. Eye movement indices, collected during item solution, were used as data.

Hypotheses

The ability to maintain information-processing efficiency, when items with new transformational rules follow sets of items governed by different rules, is hypothesized to display a significant positive relationship to aptitude test and school performance.

Procedure

The Inductive Reasoning items were administered as described above. Eye movement measures of information-processing were compared for the last item in

each subtest and the first item in the following subtest. Flexibility was reflected in the extent to which processing efficiency for each new subtest was maintained relative to the preceding subtest.

Learning

Information-processing parameters of learning were derived for subjects who participated in the aforementioned eye movement study.

Sample

The sample was comprised of 67 subjects who participated in the eye movement recording study.

Instruments

Differences in information-processing efficiency across subsets of inductive reasoning and APM items were used to assess learning. Eye movement indices, recorded during solution of the items, were used as data.

Hypotheses

Increases in processing efficiency, measured by the eye scan measures of information processing described above, are

hypothesized to be positively related to AFQT and school performance.

Procedure

Differences in information-processing efficiency were compared for the first block of five trials and the last block of five trials for the inductive reasoning items.

Cognitive Speed

Sample

The sample was comprised of 41 of the subjects who participated in the eye movement recording study. All 41 subjects completed the Choice Test while 32 subjects completed the Arrows Test (Larson, 1985).

Instruments

The Arrows Test was used as the first measure of cognitive speed. The test involved 82 trials; 41 with downward sets of arrows and 41 with right-left arrows.

The Two Choice Reaction Time Test was the second cognitive speed test used. The test included 21 trials.

Procedure

Larson described the procedure for the Arrows Test in the following paragraph.

> "Subjects were instructed to fixate on two small circles presented side by side in the center of the CRT screen. For each trial, one of the circles was replaced by an arrow, and, depending on its direction and position, the subject responded by pressing either a right or left key on the microcomputer keyboard. If the arrow pointed down, its position indicated the appropriate response. For example, if a downward arrow replaced the right circle, the right key was pressed. If a downward pointing arrow replaced the left circle, then the left key was pressed. If an arrow pointing sideways (i.e., right or left) was present, then direction became the relevant cue, while position became a distraction. If the arrow pointed right, the right key was pressed. If it pointed left, the task was to press the left key as soon as possible. RTs greater than 2 seconds were discarded and new items presented to maintain a constant number of trials per subject. A count was kept of discarded trials. The position and direction of the arrow were varied randomly."

Larson described the Two Choice Reaction Time Test as follows:

> "Subjects were presented with five squares, arranged as an "X"; e.g., one square sat in the middle, and four outer squares touched the corners of the middle square. On each trial, two of the four outer squares were illuminated. Subjects were instructed to respond according to the following rules:

1. If the illuminated squares are on the SAME SIDE (i.e., left, right, top, or bottom), then respond by pressing the left key.

2. If the illuminated squares are on OPPOSITE CORNERS, then respond by pressing the right key.

Hypotheses

Median score and standard deviation for the Arrows and Choice Reaction Time tests were hypothesized to contribute significantly to AFQT and school performance.

ANALYSES FOR ALL STUDIES

For all predictors (i.e., aptitude measures), data were analyzed using Stepwise or General Linear Model regression procedures (SAS; Helwig & Council, 1986). A standard of 10 or greater subjects per variable was used.

Criterion data were derived from two sources. First, aptitude test data were supplied by the Naval Training Center (NTC), San Diego, California. Second, school performance data were supplied on computer tape. Four measures were selected for analysis. These data were (a) contact time, (b) total number of remediations, (c) time per instructional module, and (d) final average. Contact time provides an index of the total amount of time necessary to

complete all modules of instruction. This index reflects the speed and efficiency with which examinees complete instructional sequences. The remediations measure provides an index of the number of times instructional modules must be repeated. As such, this measure reflects information-processing effectiveness, rather than efficiency per se. Final Average reflects the amount of material mastered across modules. This index provides a second measure of information-processing and learning effectiveness. Time per Module reflects the average time needed to complete a module of instruction. This index provides a second measure of learning efficiency.

With regard to predicting school performance, the new aptitude measures were used in prediction models with and without AFQT score. Without AFQT score, models reflect the criterion-related validity of the new aptitudes. Information on incremental validity is derived by examining prediction models containing new aptitude indices along with AFQT.

RESULTS

Componential Cluster: Eye Movement Recording

With respect to validating eye scan measures of information processing against the AFQT, data indicate that eye movement measures derived from the Inductive Reasoning Test account for 21% of the variance in AFQT performance, $F(5, 62) = 3.38$, $p < .01$, while eye movement measures derived from the APM account for 19% of the variance in AFQT performance, $F(5, 62) = 2.84$, $p < .05$. Models include measures of the number of encoding/rule inference row fixations (positively weighted), the number of rule application fixations (negatively weighted), confirmation fixations (negatively weighted), encoding/rule inference column fixations (positively weighted), and the number of breaks in main array processing to attempt response selection (negatively weighted).

Eye scan measures of information processing also are validated against school performance. These analyses are described below for each school performance measure.

Contact

With regard to information processing during solution of APM items, data indicate that the same model validated against AFQT accounts for 18% of the variance in Contact time using the Inductive Reasoning Test, $F(5, 62) = 2.75$, $p < .05$. A model comprised of measures of the number and percentage of confirmatory (i.e., response selection) scans (negatively weighted), the number and percentage of encoding/rule inference column scans (positively weighted), and the number of rule application row scans accounts for 20% of the variance for the APM items, $F(5, 62) = 3.13$, $p < .05$.

Information-processing measures can be coupled with AFQT to increase markedly the variance in Contact accounted for by prediction models, relative to AFQT alone. A model comprised of AFQT alone accounts for 15% of the variance in contact time, $F(1, 66) = 11.30$, $p < .001$, while models comprised of AFQT and information-processing measures account for 22-27% of the variance in Contact. Using the Inductive Reasoning Test, a model comprised of measures of AFQT, the percentage of encoding/rule inference column fixations, percentage of rule application column fixations,

the number and the percentage of confirmatory fixations accounts for 24% of the variance in Contact time, $F(5, 62) = 3.90$, $p < .01$. The increment in R^2 is not statistically significant. Using the APM items, the same model accounts for 27% of the variance in Contact, $F(5, 62) = 4.58$, $p < .001$. The increment in R^2 is significant, $F(4, 62) = 2.55$, $p < .05$.

Time Per Module

Eye scan models of information processing are validated against Time per Module. Using the Inductive Reasoning Test, data indicate that the percentage of encoding/inference column fixations, the number and percentage of confirmatory fixations, and the percentage of small scan (i.e., redundant) processes (a negatively weighted measure) account for 23% of the variance in Time per Module, $F(4, 63) = 3.61$, $p < .05$.

Next, eye movement measures of information processing are coupled with AFQT. The AFQT alone accounts for 23% of the variance in Time per Module $F(1, 66) = 19.81$, $p < .001$. Using the Inductive Reasoning Test, 35% of the variance in Time per Module is accounted for by AFQT and information-processing indices. The model is comprised of

AFQT, percentage of encoding/inference fixations, percentage of rule application fixations, number of confirmatory fixations, and number of attempts at response selection, $F(5, 62) = 6.66$, $p < .001$. The increment in R^2 is significant, $F(4, 62) = 2.86$, $p < .05$. Thirty percent of the variance in Time per Module is accounted for by the same model derived from the APM, $F(5, 62) = 5.23$, $p < .001$. The increment in R^2 is not statistically significant.

Remediation

Analysis indicates that a model, derived from the Inductive Reasoning test and comprised of the number of large (i.e., nonredundant) scans (positively weighted), small scans, rule application fixations, and the number and percentage of confirmatory fixations, accounts for 22% of the variance in number of remediations, $F(5, 62) = 3.43$, $p < .05$.

Coupling eye movement measures of information processing with AFQT, the 11% of the variance in Remediation accounted for by AFQT alone, $F(1, 66) = 8.05$, $p < .05$, is increased to 27% with a model that couples AFQT with the number of rule application fixations, the number and percentage of confirmatory fixations and the number of

diagonal scans (a positively weighted variable) taken during solution of the APM, $F(5, 62) = 4.49$, $p < .05$. The increment is significant, $F(4, 62) = 3.38$, $p < .05$.

Final Average

The eye movement models used in the analyses reported above also are used to predict each examinee's final average. The models consistently account for 17-18% of the variance in Final Average. For example, a model comprised of the number of confirmatory fixations, the total number of fixations, the percentage of fixations prior to the first attempt at confirmation, the number of attempts at confirmation, and the total number of units of processing, on the Inductive Reasoning Test items, accounts for 18% of the variance in Final Average, $F(5, 62) = 2.67$, $p < .05$. The same model, derived from the APM, accounts for 18% of the variance in Final Average, $F(5, 62) = 2.81$, $p < .05$. The AFQT alone, accounts for 2% of the variance in Final Average, failing to account for a significant amount of variance in this criterion. The increment in R^2 is significant, $F(4, 62) = 3.02$, $p < .05$. Means and standard

deviations for information-processing analyses using eye movement measures are given in Table 1. Results of the analyses are summarized in Table 2.

Insert Tables 1 and 2 about here

Componential Cluster: Multiple-Screen Technique

Indices of information processing, derived from the multiple-screen approach, are validated against AFQT. Data indicate that 46% of the variance in AFQT is accounted for by a three-variable model, derived from the Inductive Reasoning items, comprised of the number of times encoding/inference information is processed, the number of times inference preceeds rule application processing, and the total time spent processing the first screen (i.e., rule inference information), $F(3, 29) = 8.13$, $p < .001$. Means and standard deviations for these analyses are displayed in Table 3.

Insert Table 3 about here

Metacomponential Abilities

Metamemory ability first is validated against AFQT. Data indicate that 10% of the variance in metamemory ability is accounted for by AFQT, $F(1, 37) = 4.25$, $p < .05$. With regard to validating metamemory against school performance, metamemory was expected to bear relations to Time per Module and Remediations. Coupled with AFQT, the two-variable model accounts for 39% of the variance in number of remediations, $F(2, 36) = 11.38$, $p < .001$, compared to 34% accounted for by AFQT alone, $F(1, 37) = 19.13$, $p < .001$. The increment in R^2 is significant, compared to the power of AFQT alone, $F(1, 36) = 2.95$, $p < .05$. Regarding Time per Module, data indicate that metamemory, practical intelligence, and AFQT account for 45% of the variance in Time per Module, $F(3, 35) = 9.39$, $p < .001$. The increment in R^2 is significant, $F(2, 35) = 3.50$, $p < .001$. Table 4 displays means and standard deviations for these measures. Table 5 displays the results of the analyses.

Insert Tables 4 and 5 about here

Flexibility

Flexibility indices are derived for each information-processing measure by comparing the efficiency with which that aspect of processing is executed on the last item in a block of similar items to the first item in a new trial block. The rationale here is that an individual's processing is flexible to the extent that information-processing efficiency is maintained despite changes in task demands. Models comprised of indices of flexibility are validated against school performance measures.

In validating flexibility indices against school performance, a five-variable model comprised of differences in the percentages of processing resources allocated to rule inference, rule application, and confirmation processes, along with the number of rule application processes, and the total number of fixations, accounts for 25% of the variance in Contact, $F(5, 62) = 4.04$, $p < .05$. With respect to incremental validity, a five-variable model comprised of AFQT, differences in total number of fixations, number of rule application row processes, number of rule application column processes, and

number of confirmation processes accounts for 36% of the variance in contact time, $F(5, 62) = 6.92$, $p < .001$, compared to 15% accounted for by AFQT alone. The increment in R^2 is significant, $F(4, 62) = 5.09$, $p < .05$.

With regard to remediation, a four-variable flexibility model accounts for 19% of the variance in number of remediations, $F(4, 63) = 3.77$, $p < .05$. The model taps differences in the number of rule application processes, the number of times the examinee breaks ongoing processing to attempt confirmation, the total number of column processes executed, and the percentage of rule application processes executed. With regard to coupling AFQT with information-processing measures, 27% of the variance in number of remediations is accounted for by a model comprised of AFQT, differences in the percentage of rule application fixations, number of confirmatory fixations, number of rule application fixations, and the percentage of fixations prior to the first attempt at confirmation, $F(5, 62) = 4.62$, $p < .01$, while 11% of the variance in number of remediations is accounted for by AFQT alone. The increment in R^2 is significant, $F(4, 62) = 3.39$, $p < .05$. Table 6 displays means and standard deviations for the flexibility analyses.

Insert Table 6 about here

Learning

Indices of learning are derived from differences in information processing between the first and last blocks of inductive reasoning and APM items. Both eye movement and multiple-screen procedures are used.

Eye Movement Technique

For the eye movement technique, APM and Inductive Reasoning items are combined. First, this information-processing substrate of learning is validated against AFQT. A three-variable model, comprised of measures of changes over time in the amount of small chunk row processing, the percentage of total units that are large row scans, and the number of encoding/rule inference fixations, accounts for 16% of the variance in AFQT, $F(3, 63) = 3.92$, $p < .05$.

With respect to school performance, a five-variable model, comprised of measures of changes in the number of confirmation fixations, the number and percentage of small

chunk column scans, the number of large row scans, and the percentage of fixations executed prior to the first break in ongoing processing, accounts for 29% of the variance in Contact, $F(5, 61) = 4.98$, $p < .05$. When AFQT score is added to the first four variables, the model accounts for 43% of the variance in Contact, $F(5, 61) = 9.40$, $p < 001$, compared to 15% accounted for by AFQT alone, $F(1, 65) = 11.30$, $p < .05$. The increment in R^2 is significant, $F(4, 61) = 7.49$, $p < .05$.

With regard to validating learning indices against Remediations, a five-variable model comprised of measures of changes in the percentages of encoding/rule inference column fixations, row fixations, and diagonal fixations, and the numbers of column fixations and rule application fixations accounts for 28% of the variance in number of remediations, $F(5, 61) = 4.83$, $p < .05$. When AFQT is added to the first four variables, the five-variable accounts for 36% of the variance in Remediations, $F(5, 61) = 6.98$, $p < .05$. The AFQT alone accounts for 10% of the variance in Remediations, $F(1, 65) = 7.15$, $p < .05$. The increment in R^2 is significant, $F(4, 61) = 6.19$, $p < .05$.

Learning indices also are validated against Time per Module. A five variable model comprised of changes in the

numbers of confirmation fixations, breaks in processing, large row scans, the percentage of total units that are large row scans, and AFQT accounts for 37% of the variance in Time per Module, $F(5, 61) = 7.07$, $p < .05$. Twenty-two percent of the variance in Time per Module is accounted for by AFQT alone. The increment in R^2 is significant, $F(4, 61) = 3.63$, $p < .05$.

Multiple-Screen Technique

For the multiple-screen technique, items from the Inductive Reasoning Test are used. A three-variable model, comprised of differences in the total number of rule application fixations executed, the total fixations executed in rule inference activities, and the number of times rule inference preceded rule application, accounts for 51% of the variance in AFQT, $F(3, 29) = 10.31$, $p < .001$. Means and standard deviations for learning indices are presented in Table 7.

Insert Table 7 about here

Cognitive Speed

The cognitive speed measures first are validated against AFQT. Date indicate that 25% of the variance in AFQT is accounted for by a three-variable model comprised of standard deviation on the Choice test, standard deviation on the Arrows test, and number correct on the Arrows test, $F(3, 28) = 3.07$, $p < .05$. Indices of cognitive speed also are validated against school performance measures. The results of these analyses are presented below.

Contact

With regard to contact time, data indicate that 36% of the variance in Contact is accounted for by a three-variable model comprised of number correct on the Choice test, number correct on the Arrows test, and standard deviation on the Arrows test, $F(3, 28) = 5.30$, $p < .01$. Incremental validity is assessed by coupling AFQT with two cognitive speed measures. Data indicate that a model comprised of Choice number correct, Arrows standard deviation, and AFQT accounts for 48% of the variance in Contact, $F(3, 28) = 8.70$, $p <$

.001. The AFQT accounts for 29% of the variance in Contact, $F(1, 30) = 12.51$, $p < .01$. This increment in R^2 is significant, $F(2, 28) = 5.12$, $p < .05$.

Time per Module

Regarding Time per Module, data indicate that 15% of the variance in the criterion measure is accounted for by a three-variable model comprised of number correct on the Choice test, number correct on the Arrows test, and standard deviation on the Arrows test. This model fails to achieve statistical significance. Incremental validity is assessed by coupling AFQT with one cognitive speed measure. Data indicate that 48% of the variance in Time per Module is accounted for by a model comprised of number correct on the Choice test and AFQT, $F(2, 38) = 17.21$, $p < .001$, compared to 41% accounted for by AFQT alone, $F(1, 39) = 27.57$, $p < .001$. The increment does not achieve statistical significance.

Remediations

A model comprised of number correct on the Choice test and Arrows standard deviation accounts for 9% of the variance in Remediations. The model is not statistically

significant. Coupled with AFQT, the three-variable model accounts for 49% of the variance in Remediations, $F(3, 28) = 8.89$, $p < .001$, compared to 42% accounted for by AFQT alone, $F(1, 30) = 21.95$, $p < .001$. The increment in R^2 is not statistically significant.

Final Average

Data indicate that 20% of the variance in Final Average is accounted for by Choice standard deviation and Arrows number correct, $F(2, 29) = 3.72$, $p < .05$. Analysis indicates that 29% of the variance in Final Average is accounted for by a three-variable model comprised of standard deviations on the Choice and Arrows tests, coupled with AFQT, $F(3, 28) = 3.75$, $p < .05$. The AFQT alone accounts for 6% of the variance in Final Average. This one-variable model is not statistically significant. With regard to incremental validity, the increment in R^2 is significant, $F(2, 28) = 4.53$, $p < .05$. Means and standard deviations for cognitive speed measures are displayed in Table 8. The results of these analyses are presented in Table 9.

Insert Tables 8 and 9 about here

CONCLUSIONS

The data collected during this effort provide valuable information both with respect to advancing knowledge about the nature of aptitude and by providing methods and measures for increasing prediction of intelligent Navy school performance. Methodological advances are made possible by provision of (a) new methods of test administration, (b) new measures taken from aptitude tests, and (c) newly operationalized aptitude dimensions and the new tests that accompany them.

Contributions are made from all five clusters in the present framework. Conclusions for each testing approach and aptitude dimension are delineated below.

Componential Abilities

Information-processing componential skills play major roles in intelligent aptitude test and school performance. Different levels of individual differences in cognitive processes emerge as embodying important cognitive processes.

The efficiency with which individuals infer relations among item elements, apply rules to incomplete information, and confirm those rules are important to intelligent test and school performance. With regard to the allocation of information-processing resources during reasoning, in effective performance a relatively large percentage of processing resources are devoted to inferring relational rules, while small percentages of resources are allocated to application and confirmatory activities. Efficient strategies, wherein (a) rule inference and application activities precede attempts at confirmation, (b) relatively few breaks in ongoing processing occur in attempts at response selection, and (c) large, nonredundant units of information are processed at a given time, also contribute significantly to intelligent aptitude test and school performance.

Moreover, the robustness of these phenomena is indicated in that similar eye movement information-processing models predict performance for the two inductive reasoning measures during solution of which the information-processing indices are derived. These processing phenomena are not tied to a particular task. Rather, people execute the activities during solution of a

broad range of intellectual tasks (see also Dillon, in press-a, in press-b for discussions of relevant information-processing phenomena). In addition, the eye movement information-processing models predict performance across a range of school performance indices as well as predicting aptitude test performance. The models account for significant amounts of variation in the speed, efficiency, and success with which Navy personnel complete a course of training.

Significant incremental validity is realized when predictors that tap information-processing componential abilities are added to AFQT. In predicting school performance, R^2_s for models that include information-processing indices at times account for twice the variance in school performance indices than does AFQT alone.

Both eye movement and multiple-screen techniques are extremely promising. Each approach permits scientists to make powerful predictions with respect to the criterion measures of interest. Additional validation for the componential processes studied in this effort comes from

data indicating that corresponding information-processing models, derived from the two approaches, predict aptitude test performance.

The multiple-screen componential approach has very strong appeal for large-scale administration. First, R^2s derived from the technique are high. Second, test administration does not require special equipment. Test items are administered on a microcomputer.

Metacomponential Abilities

Metacognitive abilities tapping executive memory processes and practical problem-solving abilities are relevant to the manner in which individuals plan intellectual courses of action and organize resources. For this reason, the metacomponential tasks are validated against the two school measures tapping number of remediations and time per learning module. In the analyses, R^2s range from the .20s for the metacognitive dimensions alone to the mid-.40s for the metacognitive abilities coupled with AFQT. Remediations and Time per Module tap efficiency of learning (i.e., planning and organizational processes). The metacomponential processes studied play a role in this learning efficiency.

Flexibility and Learning

The information-processing substrates of learning and flexible information processing significantly are shown to contribute to intelligent aptitude test and school performance. The present effort constitutes the first reported work to (a) explicate the information-processing activities underlying the learning that occurs during testing, (b) identify the information-processing components of flexible inductive reasoning, and (c) demonstrate the role of these factors to intelligent Navy school performance.

Flexibility

Flexible information processing involves maintaining the efficiency with which information-processing stages and strategies are executed under conditions of varying task demands. Specifically, flexible information-processing occurs to the extent that the examinee is able to maintain information-processing efficiency during solution of a test item that follows a set of items with tasks demands that are similar to one another but different than the present item. While this work is just beginning, the data reported herein

are impressive. The results of the study described in this report indicate that this type of cognitive flexibility plays important roles in aptitude test and school performance. Large-scale test development efforts to date have not addressed cognitive flexibility as an aptitude dimension. The work reported herein takes the first step toward addressing this limitation.

Learning

Interest in the present effort is in decomposing learning into its information-processing substrate and predicting aptitude test and school performance from the extent to which efficient changes in these information-processing activities occur over the course of a reasoning test. Existing testing efforts have failed to take dynamic cognitive activities such as learning and flexibility into account. The work performed under this effort indicates that information-processing activities involved in learning, as well as in flexibility, play important roles in intelligent performance among Navy personnel. Given the many and varied demands that face military personnel and the dynamic nature of military

careers, learning and flexible information processing would be expected to be important aptitudes in the professional lives of Navy personnel.

Cognitive Speed

Interest in cognitive speed in the present effort is in deriving relations between indices of cognitive speed and school performance. As an initial step, the cognitive speed indices are validated against AFQT. The .25 R^2 derived from this analysis is an initial indicator of the validity of the measures. With regard to school performance, cognitive speed should be most highly related to Contact, because this measure reflects the amount of time an individual needs to complete the entire school training. The data confirm this hypothesis with an R^2 of .36 for the two-variable cognitive speed model and an R^2 of .48 when AFQT is added.

FUTURE RESEARCH

The work reported herein constitutes a set of exploratory studies. Future efforts should be directed toward cross-validation. Specific guidelines for such future research are given below.

Componential Abilities

Follow-on work should be continued with the multiple-screen componential abilities technique. A number of activities are recommended.

First, data collected under the present effort were validated against AFQT. School performance data were not yet available. These aptitude measures should be validated against school performance data as soon as these data become available.

Second, the Inductive Reasoning Test contains four sets of figural items in addition to the four sets of verbal items used in this effort. Programming efforts are underway to develop multiple-screen displays for these remaining subtests from the Inductive Reasoning Test. Data collection should continue on Navy recruits on the four verbal subtests. Data should be collected on all eight subtests as soon as programming activities are completed on the four figural tests. Data on a range of university subjects also would be desirable.

The information-processing loci of school performance should be elucidated further. Specific attention should be

directed toward the relations between particular information-processing activities and indices of school performance. Similarly, attention may be directed toward information-processing commonalities across all ASVAB subtests or across ASVAB subtests comprising general ability and speed selector composites.

Metacomponential Abilities

The metacomponential abilities studied in this effort play roles in predicting criterion measures that embody planning and organizational activities. These aptitudes should be included in ongoing testing activities when predicting criterion measures for which these organizational activities are of particular interest, or when sample sizes are sufficient to permit inclusion of metacomponential variables in addition to other variables of interest.

Learning and Flexibility

The information-processing parameters of learning and flexibility account for impressive amounts of variance in aptitude test and school performance. These measures are derived easily from the componential test administration procedures described herein. Both eye movement and

multiple-screen componential procedures should be used to derive corroborative information regarding the information-processing components of learning and cognitive flexibility that underlie intelligent school performance. Samples, from a diverse range of academic majors, are recommended for this corroborative work because a diversity of subject groups can be tested, and a range of learning criteria are available. The academic setting would afford the opportunity to acquire learning criteria across the expert novice continuum. The multiple-screen technique is recommended for Navy ratings. Given the ease with which the multiple-screen procedure can be used to gather information-processing data and the power demonstrated by the predictors, this paradigm for deriving information-processing components should be included in ongoing testing efforts.

References

Anderson, J. R. (1987). Skill acquisition: Compilation of weak-method problem solutions. Psychological Review, 94, 192-210.

Baddeley, A. D., & Hitch, G. (1974). Working memory. In G. B. Bower (Ed.), Advances in learning and motivation (Vol. 8). New York: Academic Press.

Christal, R. E. (1987). A factor-analytic study of tests of working memory. Unpublished manuscript.

Cooper, L. A. (1980). Spatial information processing: Strategies for research. In R. Snow, P-A. Federico, & W. E. Montague (Eds.), Aptitude, learning, and instruction: Cognitive process analyses. Hillsdale, NJ: Erlbaum.

Cooper, L. A. (1982). Strategies for visual comparison and representation: Individual differences. In R. J. Sternberg (Ed.), Advances in the psychology of human intelligence. Hillsdale, NJ: Erlbaum.

Cooper, L. A., & Mumaw, R. J. (1985). Spatial aptitude. In R. F. Dillon (Ed.), Individual differences in cognition (Vol. 2). New York: Academic Press.

Dillon, R. F. (1982). Individual differences in eye fixations within and between stages of inductive reasoning. (Tech. Rep. No. 82-2). Carbondale, IL: Southern Illinois University.

Dillon, R. F. (1985-a). Predicting academic achievement with models based on eye movement. Journal of Psychoeducational Assessment, 3, 157-165.

Dillon, R. F. (1985-b). Tests of three new aptitudes: Information-processing proficiency and preference, metamemory, and practical problem solving. (Tech. Rep. 85-1) Carbondale, IL: Southern Illinois University.

Dillon, R. F. (1986). Information processing and testing. Educational Psychologist, 20(3), 1-27.

Dillon, R. F. (1987-a). An information-processing framework for understanding intelligent performance. Manuscript submitted for publication.

Dillon, R. F. (1987-b). Metacomponents of intelligence. Manuscript submitted for publication.

Dillon, R. F. (1987-c). The future of aptitude testing. Invited colloquium at the Air Force Human Resources Laboratory, San Antonio, July.

Dillon, R. F. (1987-d). The multidimensional nature of cognitive flexibility. Manuscript submitted for publication.

Dillon, R. F. (in press-a). New approaches to aptitude measurement. In R. F. Dillon & J. W. Pellegrino (Eds.), Testing: Theoretical and applied perspectives. New York: Praeger.

Dillon, R. F. (in press-b). Information processing and intelligent performance. In R. J. Sternberg (Ed.), Advances in the psychology of human intelligence (Vol. 5). Hillsdale, NJ: Erlbaum.

Dillon, R. F., Lyerla, R., & Aubertin, C. A. (1987). Flexibility: Its contribution to intelligent academic performance. Paper presented at the Ninety-seventh Annual Convention of the American Psychological Association, New York, August.

Dillon, R. F., & Radtke, R. (1985). Inductive Reasoning Test. Unpublished manuscript, Southern Illinois University.

Dillon, R. F., & Reznick, R. K. (1986). Development of a new system of measurement. In Proceedings of the 1986 Meeting of the Military Testing Association. Mystic, CN: Military Testing Association.

Dillon, R. F., & Stevenson-Hicks, R. (1981). Effects of item difficulty and method of test administration on eye scan patterns during analogical reasoning. (Tech. Rep. No. 1). Carbondale, IL: Southern Illinois University, Eye Movement Research Laboratory.

Dillon, R. F., Travis, T. A., & Loschen, E. (1987). Flexibility as a measure of intelligence among psychiatry clerks. Unpublished manuscript.

Dillon, R. F., & Wisher, R. A. (1981). The use of scanning indices to predict performance on technical school qualifying tests. Applied Psychological Measurement, 5(1), 43-49.

Dillon, R. F., & Wolfe, J. H. (1988, April). Isolation of information-processing components for predicting Navy school performance. Paper accepted for presentation at the 1988 Annual Convention of the American Educational Research Association, New Orleans.

Gitomer, D. H. (1984). A cognitive analysis of a complex troubleshooting task. Unpublished doctoral dissertation. University of Pittsburgh.

Jencks, C. (1977). Who gets ahead? New York: Basic Books.

Larson, G. E. (1985). The Arrows Test. Unpublished manuscript, Navy Personnel Research and Development Center.

Lesgold, A. M., Feltovich. P. J., Glaser, R., & Wang, Y. (1981, September). The acquisition of perceptual diagnostic skill in radiology (Tech. Rep. No. PDS-1). Learning Research and Development Center, University of Pittsburgh.

Lohman, D., & Kyllonen, P. (1985). Individual differences in solution strategy on spatial tasks. In R. F. Dillon & R. R. Schmeck (Eds.), Individual differences in cognition (Vol. 2). New York: Academic Press.

Matarazzo, J. D. (1972). Wechsler's measurement and appraisal of adult intelligence (5th ed.). Baltimore: Williams & Wilkins.

McCall, R. B. (1977, July 29). Childhood IQ's as predictors of adult educational and occupational status. Science, 197, 482-483.

SAS Institute. SAS User's Guide: Statistics (Version 5 Edition). Cary, NC: SAS Institute, Inc.

Schneider, W., & Fisk, A. D. (1986). Attention theory and mechanisms for skilled performance. In R. A. Magill (Ed.), Memory and control of motor behavior. Amsterdam: North Holland.

Scribner, A. (1984). Cognitive studies of work. The Quarterly Newsletter of the Laboratory of Comparative Human Cognition, 6(1, 2).

Sternberg, R. J., & Wagner, R. K. (1986). Practical intelligence: Origins of competence in the everyday world. Cambridge: Cambridge University Press.

Wechsler, D. (1975, January). Intelligence defined and undefined: a relativistic appraisal. American Psychologist, 30(2), 135-139.

APPENDIX A

Information-Processing Indices Derived From Eye Movement Data

1. Encoding/inference fixations. These fixations are executed during formation of rules governing relations among stimulus elements. This index is the mean number of fixations across trials for an examinee occurring in the complete rows or columns of the stimulus array.

2. Rule application fixations. Rule application fixations are executed to apply rules that have been formed in the complete rows or columns of the stimulus array to the incomplete row or column of the array. This index is the mean number of fixations occurring in the incomplete row or column.

3. Confirmation fixations. Confirmation involves response selection activities. This index is the mean number of fixations occurring in the response set.

4. Breaks in main array processing. Breaks in main array processing reflect the number of times the examinee breaks main array activities to attempt response selection. The index is the mean number of times a fixation occurs in the response set, subsequent to a fixation in the main stimulus array.

5. Percentages of rule inference, rule application, and confirmation fixations. In addition to computing the number of fixations occurring in each stage of processing,

the percentages of the total number of fixations that occur in each information-processing stage also are computed.

6. Total row or column scans. Total row or column scans reflect processing of large (i.e., nonredundant) amounts of information at at given time. The mean number of total row or total column scans is defined as the mean number of times 3 successive fixations occur on three unique, consecutive points in a row or column. Either or both total row and total column scans may be computed. Row and column scans are computed as separate indices.

7. Binary row or column scans. Binary row or column scans reflect processing small (i.e., redundant) amounts of information at a given time. The mean number of binary row or binary column scans is defined as the mean number of times 3 successive fixations occur on two unique points in a row or column.

8. Diagonal scans. "Diagonal scans" is defined as the number of times per trial that three successive fixations occur from the upper left to lower right, lower right to upper left, upper right to lower left, or lower left to upper right portions of the main stimulus array.

9. Percentage of fixations prior to the first break in ongoing processing. This index taps the extent to which processing is rule governed (i.e., involves template

matching or a similar rule-based strategy) or involves nonsystematic (e.g., trial-and-error) processing. The index is the mean percentage of total fixations per trial that occur prior to the first attempt at response selection.

10. Total fixations. This index reflects overall information-processing efficiency, in that more efficient processing is marked by the need for less processing (i.e., fewer fixations). The mean number of fixations per trial is tabulated.

11. Total units. This index reflects the number of different scans necessary for response solution. The index is defined as the mean number of total and binary row and column scans, and diagonal scans.

APPENDIX B

Information-Processing Indices Derived From Multiple-Screen Data

1. Encoding/inference processing. This index reflects the mean amount of encoding/inference processing per test item. The mean number of times per test item that the examinee processes Screen 1 is tabulated for the index.

2. Strategic processing index. A measure of rule-governed processing is the number of times rule inference precedes rule application. This index is computed using the mean number of times per trial that Screen 1 is processed prior to Screen 2. Note that subsequent to processing the screens in ascending order one time, subjects may process screens in several different orders. For example, Screen 1 may be processed before or after Screen 2.

3. Encoding/rule inference time. This index is the amount of processing time spent encoding stimulus attributes and forming rules regarding the relations among stimulus attributes. This time is computed from the amount of time spent processing Screen 1. Note that this index involves elapsed time.

Table 1

Means and Standard Deviations for Eye Movement Measures of Information Processing

Information-Processing Index	Mean[a]	Standard Deviation
Inductive Reasoning Test		
Encoding/Inference Col Fixations	03.99	3.38
Rule Application Col Fixations	01.90	2.40
Encoding/Infer. Col Fixations	00.84	1.00
Confirmation Fixations	06.53	5.85
% Encoding/Inference Fixs	.32	.17
% Rule Application Fixations	.14	.11
% Confirmation Fixations	.51	.18
% Small Column Scans	.27	.21
Small Column Scans	00.84	1.00
Large Column Scans	00.38	.69
Breaks in Processing	02.03	1.35
Total Fixations	12.42	9.71
% Fix Prior to First Confirm.	.28	.17
Total Units	01.22	1.50
APM		
Encoding/Inference Row Fixations	12.20	11.64
Rule Application Row Fixations	07.62	6.61
Confirmation Row Fixations	06.89	7.08
Encoding/Infer. Column Fixations	14.26	12.94
% Encoding/Infer. Col. Fixations	.38	.18
% Rule Application Row Fixations	.25	.10
% Confirmation Fixations	.35	.20
Breaks in Processing	02.63	1.52
Diagonal Scans	00.05	.09
Total Fixations	12.42	9.71
% Fix Prior to First Confirm.	.39	.19
Total Units	03.76	3.83

[a] n=68

Table 2 1

Summary Statistics for Eye Movement Measures of Information-Processing Componential Abilities

Model	F	R^2	p
Criterion: AFQT			
Encoding/Inference Col Fixs, Rule Application Col Fixs, Confirmation Fixs, %Encoding/Inference Column Fixs, Breaks[a]	3.38	.21	<.05
Encoding/Inference Row Fixs, Rule Application Row Fixs, Confirmation Fixs, Encoding/Inference Column Fixs, Breaks[b]	2.84	.19	<.05
Criterion: Contact			
Encoding/Inference Col Fixs, Rule Application Col Fixs, Confirmatory Fixs, %Encoding/Inference Column Fixs, Breaks[a]	2.75	.18	<.05
Rule Application Row Scans, Confirmatory Fixs, Encoding/Inference Column Scans, %Encoding/ Inference Column Scans, %Confirmatory Scans[b]	3.13	.20	<.05
Criterion: Time per Module			
%Encoding/Inference Col Fixs, Confirm Fixs, % Confirmatory Fixs, %Small Scans[a]	3.61	.23	<.05
Criterion: Remediations			
Rule Applic, Confirm Fixs, %Confirm Fixs, Large Scans, Small Scans[a]	3.43	.22	<.05

Table 2 (Cont.)

Model	F	R^2	p
Criterion: Final Average			
Confirmatory Fixs, Total Fixs, %Fix Prior to First Attempt at Confirmation, Total Units[a]	2.67	.18	<.05
Confirmatory Fixs, Total Fixs, %Fix Prior to First Attempt at Confirmation, Total Units[b]	2.81	.18	<.05

Model	F	R^2	p	Model	F	R^2	p	Incr F	p
AFQT	11.30	.15	<.001	AFQT, Confirm, %Encod/ Inference, %Rule Applic, Confirmation Fixs[a]	3.90	.24	<.01	1.83	ns
				AFQT, Confirmn, %Encod/ Inference, %Rule Applicatn, Confirmatory Fixs[b]	4.58	.27	<.001	2.55	<.05
Criterion: Time per Module									
AFQT	19.81	.23	<.001	AFQT, %Encod/Infer Col Row, %Rule Application, Confirm Fixs, Breaks[a]	6.66	.35	<.001	3.00	<.05
				AFQT %Encod/Infer Row, %Rule Applic, Confirm Fixs, Breaks[b]	1.59	.30	<.001	1.55	ns
Criterion: Remediations									
AFQT	8.05	.11	<.01	AFQT, Rule Applic, Confirm, Diagonal Fixs, %Confirmatory Fixations[b]	4.49	.27	<.05	3.38	<.05

[a]Eye movement data are recorded during solution of the Inductive Reasoning Test.

[b]Eye movement data are recorded during solution of the APM.

Table 3

Means and Standard Deviations for Multiple-Screen Measures of Information Processing

Information-Processing Index	Mean[a]	Standard Deviation
Encoding/Rule Inference Screens Processed	3.54	.07
Number of Times Rule Governed Strategy Component Executed	7.90	2.07
Time Spent in Encoding/	54.42 sec	7.63 sec

[a]n=35

Table 4

Means and Standard Deviations for Metacognitive Tests

Test	Mean[a]	Standard Deviation
Metamemory	49.85	7.82
Practical Intelligence	114.97	13.38

[a] n=39

Table 5

Metacognitive Measures:
Multiple Correlations of Predictors With Criteria

No.	Predictor Set	Criterion: Time per Module	Criterion: Remediations
1	AFQT	.36*	.34*
2	AFQT & Measures	.45*	.39*
	Validity Increment	.09*	.05*

Table 6

Means and Standard Deviations for
Information-Processing Measures of Flexibility

Information-Processing Index	Means[a]	Standard Deviation
Rule Application Row Flex	-0.63	2.80
Confirmation Flex	-1.06	6.61
Total Fixations Flex	-2.10	11.25
% Encoding/Inference Flex	- .02	.27
% Rule Applic. Row Fixations Flex	- .07	.18
% Rule Applic. Column Fixations Flex	- .04	.30
%Confirmation Fixs Flex	- .00	.35

[a] n=68

Table 7

Means and Standard Deviations for
Information-Processing Measures of Learning

Information-Processing Index	Mean[a]	Standard Deviation
Encoding/Rule Inference Row Learning Fixations	-1.57	8.64
Rule Application Row Learning Fix	-1.35	3.62
Confirmation Learning Fixations	0.77	7.10
Encod/Infer Row Fixations Occurring Before Rule App Fix	-0.08	1.77
%Encoding/Inference Row Learning Fixations	.00	.20
%Rule Application Row Learning Fixations	- .04	.13
Row Learning Fixations	-0.40	2.10

[a]n=67

Table 8

Means and Standard Deviations for Cognitive Speed Measures

Cognitive Speed Index	n	Mean	Standard Deviation
Choice Correct	41	20.41	1.32
Choice Standard Deviation	41	164.69 sec	72.36 sec
Arrows Correct	32	79.31	2.29
Arrows Standard Deviation	32	133.85 sec	48.75 sec

Table 9

Cognitive Speed:
Multiple Correlations of Predictors With Criteria

No.	Predictor Set	Criteria			
		Contact	Time/Module	Remeds	FSG
1	AFQT	.29*	.41*	.42*	.06
2	Cognitive Speed	.36*	.15	.09	.20*
3	AFQT & Cog Speed	.48*	.48*	.49*	.29*
	Validity Increment	.19*	.07	.07	.17*